

Preliminary and incomplete

What Happens when Technology Improves?
Results from a New Quarterly Series on Utilization-Adjusted Total Factor Productivity

John Fernald*

Federal Reserve Bank of San Francisco

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Abstract: This paper extends the literature that explores the dynamic response of the economy to technology shocks. The shocks used are “direct” measures of aggregate technology, measured as Solow residuals (aka , total factor productivity, or TFP) with an adjustment for variations in labor effort and capital’s workweek. In addition, motivated by the growing body of literature on investment-specific technical change, the quarterly series is also decomposed into utilization-adjusted investment TFP and consumption TFP. As in Gali (1999) and Basu, Fernald, and Kimball (2006), hours worked fall for several periods following an improvement in technology.

Keywords:

* Contact information: john.fernald@sf.frb.org.

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This paper extends the literature that explores the dynamic response of the economy to technology shocks. The shocks used are “direct” measures of aggregate technology, measured as Solow residuals (aka , total factor productivity, or TFP) with an adjustment for variations in labor effort and capital’s workweek. In addition, motivated by the growing body of literature on investment-specific technical change, the quarterly series is also decomposed into utilization-adjusted investment TFP and consumption TFP. As in Gali (1999) and Basu, Fernald, and Kimball (2006), hours worked fall for several periods following an improvement in technology.

The first contribution of the paper is the dataset itself, which is updated quarterly and easily downloadable.¹ Quarterly measures of TFP (with or without a utilization adjustment) are frequently useful as in input into empirical work or for evaluating models. There appear to be no easily accessible, high-frequency measures of TFP. The growth-accounting literature generally presents TFP estimates using annual data. For example, the Bureau of Labor Statistics produces such a series at an annual frequency, generally with a long lag. Dale Jorgenson has also produced such an annual series, along with the industry data that underlie it.

Relative to the existing literature, the main contribution of this paper is to develop such a direct measure at a quarterly frequency. With simplifying assumptions (e.g., if one assumes homogenous capital and labor), it is relatively easy to construct measures of TFP, and many papers take this approach. In more realistic cases (e.g., where a high school dropout does not have the same marginal product as a Ph.D.; or where the quarterly service flow from a computer is not the same as the flow from a an office building), there are some technical issues that macroeconomic literature often wishes to abstract from but which, nevertheless, have implications for measurement and interpretation. The data in this paper can be used to obtain measures that most closely match the desired concept.

¹ The current vintage of the data is posted at

<http://www.frbsf.org/economics/economists/jfernald.html>.

The measures in this paper are most closely related to those in Basu, Fernald, and Kimball (BFK, 2006) and Basu, Fernald, Fisher, and Kimball (2011). Those papers develop direct aggregate technology series by building up from an industry data, which are available only annually. In contrast, this paper takes a top-down approach. The top-down approach is dictated by the desire for a quarterly series, where aggregate TFP itself can be estimated fairly carefully from quarterly data.

The utilization adjustment in this paper follows BFK fairly directly. The data necessary to apply their utilization adjustment—hours per worker at an industry level as a theoretically derived proxy for variations in labor effort and capital’s workweek—are available at high frequency. The key parameter estimates (from the proxy for variations in utilization) need to be estimated from annual data. This paper uses the BFK estimates of the key industry parameters, which ensures that, when annualized, the utilization measure in this paper is very close to theirs.

There are some downsides to having a quarterly measure. Most notably, this paper imposes constant returns to scale. In contrast, BFK and BFFK allow for non-constant returns at an industry level—and, indeed, find evidence of heterogeneity across sectors. In addition, the top-down approach does not allow us to control for various reallocation effects, i.e., where the same factor of production has a different value of its marginal product in different uses. Any reallocation effects would be included in the quarterly utilization-adjusted TFP measure.²

In addition to the data set itself, the second contribution of this paper is the empirical results on the dynamics of the economy’s response to technology improvements. As in Gali (1999) and BFK (2006), technology improvements are, on average, broadly contractionary—hours worked fall, for example.

² Basu and Fernald (2001, 2002) for a discussion of reallocation effects in the context of growth-accounting per se, or Hsieh and Klenow (20xx) for a discussion of effects on the level of TFP.

The literature on investment-specific technical change that follows Greenwood, Hercowitz, and Krusell (1996) has highlighted that macroeconomic effects of technology shocks should depend on the final goods sector that the shock hits. Basu, Fernald, Fisher, and Kimball (2011) highlight that different models have very different implications for the role of shocks that affect the ability to produce consumption goods versus investment goods.

Like BFFK, this paper also finds that investment-sector technology improvements are sharply contractionary. [In quarterly data, it is harder to identify the effects of consumption-technology improvements..].

Section I of the paper discusses the theory that underlies the measurement of TFP. Section II summarizes the data that are used (with more detailed discussion in the appendix). Section III provides results. The paper then concludes with broader discussion of uses of these data and results. The appendix contains greater detail on the data. .

I. Method

Aggregate TFP

Suppose we model aggregate activity with an aggregate production function:

$$Y_t = F(Z_t \cdot K_{1,t-1}, K_{2,t-1}, \dots, K_{J,t-1}, E_t \cdot L_{1,t}, H_{2,t}, \dots, H_{N,t}, A_t)$$

K is capital input, which is an aggregate of the service flow, $K_{j,t-1}$, from the J types of capital (e.g., computers, transportation equipment, structures, and land); the service flow in period t is proportional to the stock of that type of capital at the end of period $t-1$. L is labor input, which is an aggregate of the hours worked, H_j , by N types of workers (e.g., female 40-year-old college-educated professionals, male 22-year old high-school dropouts, and so forth). Z is capital utilization (e.g., the average workweek of capital) and E is effort per unit of labor. A is technological change.

Suppose there is a representative firm that takes capital rental rates, R_j , and wages, W_n , as given and charges a markup μ of price over marginal cost. The first-order conditions for cost minimization imply that output elasticities are a markup over cost shares, i.e.,

$\partial Y_t / K_{j,t} \cdot K_{j,t} / Y_t = \mu \cdot R_{j,t} K_j / P_t Y_t = \mu \gamma_{j,t}$ and $\partial Y_t / H_{n,t} \cdot H_{n,t} / Y_t = \mu \cdot W_n H_n / P_t Y_t = \mu \beta_{n,t}$. $\gamma_{j,t}$ is the share of capital of type j , where $\sum_j \gamma_{j,t} = \alpha_t$, and $\beta_{n,t}$ is the share of labor of type n , where (with zero economic profits) $\sum_n \beta_{n,t} = (1 - \alpha_t)$. In the data, we will take capital's share α_t as a residual, which enforces that capital and labor's shares sum to one. Note that, in this setup, differences in factor prices imply differences in marginal products.

Composition-adjusted growth in capital and labor input are:

$$\begin{aligned} \Delta \ln K_t &\equiv \sum_j (\gamma_{j,t} / \alpha_t) \Delta \ln K_{j,t-1} \\ \Delta \ln L_t &= \sum_n \beta_{n,t} / (1 - \alpha_t) \Delta \ln H_{n,t} \equiv \Delta \ln Q_t + \Delta \ln H_t, \text{ where } \Delta \ln H_t = \Delta \ln \sum_n H_{n,t} \end{aligned}$$

These definitions weight different types of inputs using marginal products. Markups hit all factors equally, so that they do not enter these definitions. Labor input is explicitly decomposed into raw hours worked, H , and “quality,” Q , where Q is implicitly defined in the second equation as the difference between growth in labor input and growth in raw hours. The reason for explicitly breaking out quality and quantity of labor is that they come from different sources that rely on different methods.

Differentiating the production function and dropping time subscripts (for simplicity) yields:

$$\Delta \ln Y = \mu(\alpha \Delta \ln K + (1 - \alpha) \Delta \ln(L)) + \Delta \ln U + \Delta \ln A, \quad (1)$$

where $\Delta \ln U \equiv \mu - \alpha \Delta \ln Z + (1 - \alpha) \Delta \ln E$. We normalize the elasticity of F with respect to technology, A , to equal unity.

We define TFP and utilization-adjusted TFP, $\Delta \ln A^{TFP}$, as:

$$\Delta \ln TFP \equiv \Delta \ln Y - \alpha \Delta \ln K - (1 - \alpha) \Delta \ln L = \Delta \ln U + \Delta \ln A^{TFP} \quad (2)$$

$\Delta \ln A$ is thus utilization-adjusted TFP growth.

In the context of a specific model, TFP is often defined using (1), i.e., as the multiplicative technology term in the production function, A . Under standard conditions (constant returns to scale, perfect competition, and identical factor prices for all producers), the statistical definition corresponds to the multiplicative technology term in the model. Hulten (1978) shows that—in a model with heterogeneous, constant-returns, perfectly competitive producers facing identical factor prices—this definition of aggregate TFP corresponds to the outward shift in society’s aggregate production possibilities frontier.

However, in some models (e.g., with markups, possibly heterogeneous across producers, of price above marginal cost, or with factor adjustment costs that lead the shadow cost of inputs to differ across firms), aggregate TFP and aggregate technology are not the same—even in the absence of variable factor utilization; see, for example, Basu and Fernald (2001). Even then, the statistical definition of $\Delta \ln TFP$ is still an object that can be defined in the model and compared with the data.

Any failures of aggregation (so that there is no aggregate production function of the form posited here) will, of course, show up in utilization-corrected TFP growth. Similarly, if observed factor shares do not equal output elasticities—as in the case with imperfect competition—then those effects will also show up in utilization-adjusted TFP growth. Using detailed industry data at an annual frequency, BFK control for these factors to develop a “purified” technology measure. As noted above, these necessary data are available only with a long lag, and are not available quarterly.

Investment versus consumption

Considerable recent literature looks at the role of “investment-specific technical change,” as in Greenwood, Hercowitz, and Krusell (1997). Basu, Fernald, Fisher, and Kimball (2009) argue that a more natural (though equivalent) breakdown is along the lines of equipment investment versus consumption. To allow an analysis along these lines, I use relative prices to decompose aggregate TFP into TFP for the equipment-investment-sector and for the consumption-sector. “Consumption” in this context means everything other than equipment investment and consumer durables.

In particular, we can take aggregate TFP growth (defined in equation 1) as, identically, equal to:

$$\Delta \ln TFP = w^I \Delta \ln TFP^C + (1 - w^I) \Delta \ln TFP^I ,$$

where w^j is the share of sector j (consumption, C, or investment, I).³ If producers in both sectors have equal factor shares, pay the same factor prices, and have indirect business taxes that are a constant proportion to one another,⁴ then changes in relative TFP equal changes in relative prices:

³ As Basu and Fernald (2002) discuss, there are also reallocation effects related to differences in factor prices across sectors. The data are not available to measure those terms in quarterly data, so we include them in sectoral TFP itself.

⁴ Under zero profits, which we maintain, the value of output equals the value of input:

$P^m Y^m = W^m L^m + R^m K^m$, where $m \subset$ Investment, consumption . Differentiating logarithmically, assuming equal factor shares in the two sectors, yields: $\Delta \ln Y^m - \alpha \Delta \ln K^m - (1 - \alpha) \Delta \ln L^m = \alpha \Delta \ln R^m + (1 - \alpha) \Delta \ln W^m - \Delta \ln P^m$.

$$\Delta \ln TFP^I - \Delta \ln TFP^C = \Delta \ln P_C - \Delta \ln P_I \quad (2)$$

$\Delta \ln P_I$ is the prices of equipment and software combined with consumer durables; $\Delta \ln P_C$ is the price of business output less the price of investment.⁵ That is, if $\Delta \ln P$ is growth in the price of business output, then $\Delta \ln P_C$ is defined implicitly by $\Delta \ln P = (1 - w^I) \Delta \ln P_C + w^I \Delta \ln P_I$.

I impose (2) quarter-by-quarter, which is a strong assumption. BFFK find that passthrough of relative changes in TFP to relative prices is not immediate, even in annual data. However, the link between relative TFP and relative prices is much closer than the link between relative *technology* and relative prices, where full pass-through takes three or more *years*. Much of the slippage, however, reflects margins such as utilization, which drive a gap between measured TFP and technology. We turn to utilization next.

The left-hand-side is measured TFP; the right-hand-side is share-weighted real factor prices. Assuming factor prices are equal in the two sectors implies the equation in the text. Indirect business taxes drive a wedge between producer and purchaser prices but do not affect the relationship as long as log-changes over time are the same in both sectors. See Basu, Fernald, Fisher, and Kimball (2009) for more discussion of the relationship between relative prices and relative technologies.

⁵ The price of business output less the price of BFI, $\Delta \ln P_C$, is defined implicitly by

$$\Delta \ln P = w^C \Delta \ln P_C + w^I \Delta \ln P_I .$$

Utilization

Basu, Fernald, and Kimball (2006) seek to estimate “purified” Solow residuals by controlling for non-technological factors that could affect these residuals. In particular, BFK estimate a Hall (1990)-style regression on industry-level data, which allows for non-constant returns to scale and imperfect competition as well as variable factor utilization. In quarterly data, it is not possible to implement the full BFK estimation. However, we can implement part of it, in order to decompose TFP growth into utilization change, $\Delta \ln U$, and utilization-adjusted TFP, $\Delta \ln A^{TFP}$.

A large literature suggests that unobserved variations in factor utilization are important over the business cycle.⁶ For example:

- Firms hoard labor in downturns, because they do not want to fire workers who have valuable skills that they will need in the future;
- firms reduce the workweek of capital, because it isn’t worth paying a shift premium to get people to work at night or because the capital will depreciate as it is worked more intensively;
- firms shut factories because, in a putty-clay world, the value of the output that can be produced from using the capital doesn’t cover the variable costs in terms of labor and materials.

The challenge is to derive a suitable proxy for unobserved output utilization variation, $\Delta \ln U$. BFK consider a firm that seeks to minimize the present discounted value of costs for any given path of output. There is a convex cost of adjusting the quasi-fixed factors—capital stock and number of employees. In addition to this extensive margin, firms have access to various intensive margins: Hours worked per employee; effort required of employees per hour of work; and the workweek of capital (e.g., varying the number of shifts). BFK show conditions in which the relatively easily observed margin (hours per worker) proxy for the two difficult-to-observe margins (labor effort and capital’s workweek). In particular, the basic idea behind using growth in hours-per-worker to the regression as a proxy for unobserved variations in labor effort and capital’s workweek is that a cost-minimizing firm operates on all margins—whether observed or unobserved—simultaneously. As a result, changes in observed

⁶ See Basu, Fernald, and Kimball (2006) for references.

margins can proxy for otherwise-unobserved utilization changes. If labor is particularly valuable, for example, firms will work existing employees both *longer* (observed hours per worker rise) and *harder* (unobserved effort rises).

In particular, BFK estimate (with demand-side instruments) the following equation on industry data:

$$\Delta \ln Y_i = \mu_i \Delta \ln X_i + \beta_i \Delta \ln(H^i / N^i) + \Delta \ln A_i$$

where

$$\Delta \ln X_i = s_{Ki} \Delta \ln K_i + s_{Li} \Delta \ln L_i + s_{Mi} \Delta \ln M_i$$

X_i is revenue-share-weighted inputs of capital, labor, and intermediate-inputs, M_i . $\ln(H^i / N^i)$ is hours/worker (note that total hours, as well as labor quality, is already included in labor input, L_i). The coefficient β_i , which can be estimated, relates observed hours growth to unobserved variations in labor effort and capital's workweek. That coefficient incorporates various elasticities including, in particular, the elasticity of unobserved effort with respect to hours, from the implicit function relating them (which came out of optimization).

To create a quarterly utilization series, we use the estimated industry β_i coefficients, applied to quarterly data. We first detrend the data using the Christiano-Fitzgerald bandpass filter to remove components of hours/worker at frequencies lower than 2 and exceeding 32 quarters. We then use the average industry weights from BFK to create an aggregate quarterly utilization measure.

II. Data Sources

Key data sources for estimating (unadjusted) quarterly TFP for the U.S. business sector are the following:

- (i) Output and hours: The BLS productivity and cost release provides data on $\Delta \ln Y$ and $\Delta \ln H$ for the business sector (which is what the quarterly capital data most closely correspond to). These data are available from 1947:1 on.
- (ii) Capital input: The quarterly national income and product accounts (produced by the Bureau of Economic Analysis, BEA) provide investment data for 7 types of non-residential equipment, software, and structures. I use these data to create perpetual-inventory series on (end of previous quarter, i.e., beginning of current quarter) capital stocks by different type of asset. Weighting growth in these disaggregated types of capital with estimated factor payments (which, in turn, use estimated user costs) gives quarterly capital input $\Delta \ln K$.
- (iii) Factor shares: I interpolate the annual data on factor shares, α and $(1 - \alpha)$, from the BLS multifactor productivity database.⁷
- (iv) Labor composition: From 1979:1 on, I use estimates that follow Aaronson and Sullivan (2001), as updated by Bart Hobijn and Joyce Kwok. Prior to 1979, I interpolate and extrapolate annual data from BLS multifactor productivity data.
- (v) Investment versus consumption technology: To decompose aggregate TFP along final demand lines, I create two Tornquist price indices from NIPA data. The first is the price of “equipment,” defined as equipment, software, and consumer durables. The second is the price of non-durable “consumption,” defined as the price of business output less the price of equipment (which, of course, comprises equipment, software, and consumer durables). I assume the relative price of equipment investment corresponds, quarter-by-quarter, to TFP in consumption relative to equipment investment. This measure of relative TFP is not, of course, necessarily equal to technology change period by period.

⁷ Results were little affected in experiments with other reasonable choices, such as using national accounting data.

To estimate a quarterly series on utilization, the key data source is the following:

- (vi) Industry and aggregate utilization: Hours-per-worker (H^i / N^i) by industry from the monthly employment report of the BLS. These are used to estimate a series on industry utilization $\Delta \ln U_i = \beta_i \Delta \ln(H^i / N^i)$, where β_i is a coefficient estimated by BFK. I then calculate an aggregate utilization adjustment as $\Delta \ln U = \sum_i w_i \Delta \ln U_i$, where w_i is the industry weight from BFK (taken as the average value over the full sample).⁸
- (vii) Investment and consumption utilization: I use input-output data from Basu, Fernald, Fisher, and Kimball (2009). They suggest that a reasonable measure of equipment investment utilization change is $\Delta \ln U^I = [b_{J,1} \ b_{J,2} \ \dots]' [I - B]^{-1} [\Delta \ln U_1 \ \Delta \ln U_2 \ \dots]'$:

- $[b_{J,1} \ b_{J,2} \ \dots]$ is a row vector of commodity shares of equipment investment and consumer durables. For example, if commodity 1 were electrical equipment, then $b_{J,1}$ would be the share of electrical equipment in total equipment investment and consumer durables).
- B is the intermediate-input shares from the use matrix (where element b_{ij} is the share of commodity j in industry i).
- $[\Delta \ln U_1 \ \Delta \ln U_2 \ \dots]'$ is the vector of industry utilization changes.

For the industry weights, $[b_{J,1} \ b_{J,2} \ \dots]' [I - B]^{-1}$, I use the average value over the BFFK sample of 1961-2004. Consumption (“other”) utilization is implicitly defined by the assumption that total utilization change is a share-weighted average of utilization in equipment investment and consumption, so that $\Delta \ln U^C = \Delta \ln U - w^I \Delta \ln U^I / (1 - w^I)$.

As described in the next section on details of implementation, several other data sources are used in constructing the quarterly series. These include several series that are interpolated—and, for the most recent periods, extrapolated—from annual estimates of the BLS (e.g., labor quality and inputs of land). They also include industry weights that were used by BFK to aggregate the industry utilization series.

⁸ $w_i = w_i^V / (1 - s_{Mi})$, where w_i^V is the industry’s weight in aggregate value added, and s_{Mi} is the share of intermediate inputs.

As already noted, the resulting series differs conceptually from the BFK purified technology series along several dimensions. BFK use detailed industry data to construct estimates of industry technology change that control for variable factor utilization and deviations from constant returns and perfect competition. They then aggregate these residuals to estimate aggregate technology change. Thus, they do not assume the existence of a constant-returns aggregate production function. The industry data needed to undertake the BFK estimates are available only annually, not quarterly. As a result, the quarterly series estimated here does not control for deviations from constant returns and perfect competition.⁹

As BFK (and, earlier, Basu and Fernald, 1997) argue, even if the typical industry has close to constant returns, there is substantial heterogeneity across industries, and this heterogeneity generates reallocation terms that have aggregate implications and that affect estimates of aggregate dynamics. The quarterly series here does not control for these aggregate reallocation terms.

III. Dynamic Responses of the Economy [Extremely incomplete so far]

First, how similar is the non-utilization-adjusted series to the annual multifactor productivity (MFP) series produced by the Bureau of Labor Statistics? Figure 1 compares the two. It takes the quarterly TFP series, and annualizes it to make it comparable to the BLS data on the business economy.¹⁰

As Figure 1 shows, the quarterly estimates (in blue) correspond closely with the “official” BLS data (red). The main quantitative reason for the small gaps comes from the capital input data, which differ slightly. The BLS uses much more disaggregated investment data, which are available only annually. In

⁹ The output data also differ, both in vintage and data source, from the annual data used by BFK.

¹⁰ Note that annual average data is not the same as taking a four-quarter average. Instead, the data are converted to a levels series, averaged over calendar years, and then the annual-average growth rate is calculated.

addition, they make slightly different depreciation assumptions; and their user-cost assumptions (which weight types of capital) are likely to differ somewhat.

Nevertheless, the clear conclusion from the Figure is that the quarterly series is a good high-frequency measure that corresponds to the lower-frequency BLS MFP data. Given that the MFP data are considered to be very high quality growth-accounting measures, this comparison suggests that the quarterly series is also very high quality.

Second, what is the effect of the utilization correction? Figure 2 shows aggregate TFP, with and without a utilization adjustment. The red line in Figure 2 shows that standard TFP growth always turns negative in recessions. The 2007-09 recession was no exception. The sharpest declines in measured TFP occur in the deepest recession, as in 1973-75, 1981-82, and 2007-09.

However, this decline in measured TFP does not mean that innovation has reversed or that the economy has become less efficient. Instead, a longstanding explanation attributes this fall in TFP during recessions to difficult-to-quantify variations in labor effort and intensity of capital use. Firms, for example, may hesitate to fire skilled workers they will need once the economy recovers, because they will lose valuable firm-specific skills and knowledge. Instead, firms are likely to reduce overtime (which reduces measured labor input) and also, less obviously, the required effort of each worker (which is difficult to measure). At the same time that firms vary the intensity with which they use labor, they are also likely to vary capital utilization—that is, the intensity with which machinery and structures are used, most obviously the number of hours per week the capital actually operates. (e.g., Shapiro 1996)

The blue line in Figure 2 controls for the effects of varying utilization on measured TFP as discussed in the previous section. There is no longer a clear sense that technology turns negative in recession.

Third, are the blue shocks a reasonable measure of technology? After all, they control for some of the cyclical influences, but not necessarily all of them. Consider Granger-causality tests, using the Hall-Ramey instruments as exogenous demand-shifters. Table 2 shows...

Finally, impulse responses in Figure 3 suggest that, when technology improves, hours worked fall. The bottom panel shows the responses to investment technology and consumption technology. (Each VAR is run with only one of the technology measures in it. Later drafts will explore this issue further. The decline is quite sharp using investment technology, but not statistically different from zero using consumption technology. These results are consistent with BFFK.

IV. Conclusions

This paper discusses the measurement of “purified” technology shocks at a quarterly basis, as well as identifying the responses of the economy to technology shocks. This approach is similar to that in Basu, Fernald, and Kimball (2006). However, the BFK series are at an annual frequency. Although the data necessary to undertake a complete BFK correction are not available quarterly (e.g., to control for cyclical effects related to non-constant returns to scale or reallocation effects), it is possible to correct quarterly TFP for variations in factor utilization. The utilization adjustment follows BFK (2006), who use hours per worker as a proxy for utilization change (with an econometrically estimated coefficient) at an industry level. The input-output matrix was used to aggregate industry utilization change into investment and consumption utilization change, as in Basu, Fernald, Fisher, and Kimball (2011).

The paper then explores the dynamic response of the economy to technology shocks. As in BFK and Gali (1999) and much of the related literature, technology improvements appear contractionary for hours worked.

[Expand discussion of results.]

Even apart from the substantive results, a high quality quarterly series on TFP (with or without a utilization adjustment) is of interest. For example, one possible use is to compare the estimated shocks

with those that come from estimating a fully specified dynamic general equilibrium model. Many authors estimate such models, which are often complex, using Bayesian methods. The full-information approach of these models is, of course, preferable in an efficiency sense—if one is sure that one has specified the correct structural model of the economy with all its frictions. If the model is not properly specified, however, it is unclear how reliable the shock (and parameter) estimates are. The approach in this paper uses a much more limited-information method to estimate the technology shocks. It is more transparent in its identification and robust in its method, since it does not rely on specifying correctly the full model of the economy, but only small pieces of such a model. Furthermore, there is no need to assume that true technology shocks are orthogonal to other structural shocks, such as monetary policy shocks.

Indeed, one can feed the shocks from this paper into small, plausibly-calibrated models of fluctuations. Basu and Fernald (2009) use this approach to estimate how potential output fluctuates over time. At worst, our method should provide a robust, albeit inefficient, method of assessing some of the key findings.

Finally, it is worth asking whether this paper is useful, in light of the worst financial crisis since the Great Depression? After all, the crisis surely did not reflect unusually large technology shocks—based on anecdotal evidence from the crisis itself, or based on the empirical estimates of technology in this paper. There are, nevertheless, at least two reasons for focusing on technology shocks and their impact on the economy. First, models with financial frictions may have implications for how technology shocks affect the economy, much in the way that many papers have looked at how other frictions (e.g., price rigidities) affect the economy's response to technology shocks. Hence, the impulse responses can be informative about models. Second, in estimating DSGE models of the financial crisis, it is easy to find that investment-specific “technology” shocks appear to be an important driver of the crisis. These models often do not have an explicit financial sector, so financial shocks have to show up elsewhere in the model. In typical modeling environments, however, true “technology” shocks are difficult to differentiate from the effects of financial frictions (see Justiniano and Primiceri, 2008). By providing additional, relatively

direct measures of the investment technology component, model estimation may be better able to differentiate the estimated part that reflects financial frictions as opposed to technological improvements in the investment sector.

Appendix: Details on Data and Variable Construction

Labor Productivity

The main source for the quarterly TFP series is business-sector labor productivity data produced by the BLS each quarter. The data begin in 1947:1, and new data are available approximately five weeks after the end of each quarter. At that point, it is possible to produce an estimate of the quarterly TFP series. The BLS itself produces an annual TFP series, but only with a lag of several years.

Factor Shares

We need relative shares in revenue for labor and capital. I interpolate the annual shares reported in the BLS multifactor productivity dataset (using a cubic spline). Those data begin in 1948. For quarters before and after the multifactor-productivity data are available, I assume the annual shares are unchanged from their first/last value before implementing the cubic spline. (The series has relatively modest variation, so this assumption is likely to be innocuous.)¹¹

In principle, one could estimate the quarterly factor shares from national accounting data. There are several challenges in trying to calculate the shares properly from national-accounting data alone. First, we need to decompose proprietor's income into labor and capital income. With national accounts data, we could assume that the factor shares are the same as for non-proprietors. Alternatively, we could go beyond national accounting data, as both the BLS (for their multi-factor-productivity data) and Jorgenson do, and impute a wage to proprietors based on their observed demographic characteristics in the Current Population Survey. The latter method is probably more appropriate, but requires detailed data and computation to implement.

¹¹ If implicit contracts are important, then the observed fluctuations in factor payments might not reflect actual fluctuations. Indeed, the business-cycle fluctuations in factor shares might not be allocative at all, arguing for simply assuming Cobb-Douglas and using constant factor shares.

Second, business taxes are a challenge. Define PY as nominal business-sector GDP, which is measured using market prices, i.e., from the point of view of purchasers. For factor shares, we need revenue from the point of view of the producer. Let TPS be taxes on production less subsidies (this replaces the former name, indirect business taxes). We want to exclude sales and excise taxes, which are not a payment to a factor. We do want to include motor vehicle and property taxes, which are part of the cost of using capital. And we want to include subsidies, which are revenue to the producer.

On an annual basis, the BEA (NIPA Table 3.5) provides the components of taxes on production. Unfortunately, for these purposes, property taxes include the property taxes of owner-occupied housing, since the BEA considers that a “business” (though owner-equivalent rent is not included in business output in the BEA’s sectoral decomposition of GDP).

In any case, it is a bit of a challenge to get all the pieces to calculate factor shares quarterly. Interestingly, taking $PY-TPS$ provides a reasonably good approximation in annual data to factor-cost in the BLS MFP data. When necessary to calculate the implied interest rate (needed for the cost of capital, below), I use this value as an approximation to total factor cost. That said, capital-input measures do not appear too sensitive to reasonable variation for the value of nominal capital payments used to compute the implicit nominal interest rate.

Capital Input

We have to aggregate heterogeneous capital goods into a capital-input (or capital services) measure, K . I use quarterly estimates of the stocks of nine types of capital, including six categories of equipment and software, plus structures, inventories, and land. For equipment, software, and structures, I use detailed investment data, I_j , with assumed (annual) geometric depreciation rates, δ_j , in parentheses:¹²

¹² For equipment and structures, I obtain these investment data from NIPA Tables 1.5.5 (nominal) and 1.5.6 (chain-weighted). This level of disaggregation allows a consistent time series since the 1940s. It is possible to obtain more detailed quarterly investment data, but generally for a shorter sample period. The depreciation rates

- (1) Computers and peripheral equipment (31.5 percent);
- (2) Software (44 percent)
- (3) Other information processing equipment¹³ (13.3 percent)
- (4) Industrial equipment (9.3 percent);
- (5) Transportation equipment (12.8 percent);
- (6) Other equipment (13.9 percent);
- (7) Structures (2.4 percent).

For inventories (with a depreciation rate of 0 percent), I use direct estimates of the quarterly stocks from NIPA. For land, I interpolate the annual values from the BLS multifactor productivity dataset.

For the categories of equipment and software and for structures, I calculate beginning-of-quarter (end of previous quarter) capital stocks $K_{j,t-1}$ using the perpetual inventory method, so that

$K_{j,t-1} = (1 - \delta_j)K_{j,t-2} + I_{j,t-1}$. As an initial estimate of the capital stock, I use end-of-year BEA estimates of the stock of each type of capital as of the end of 1946 (i.e., beginning of 1947:1).

According to the BLS, land accounts for approximately 11 percent of capital income in the business sector.¹⁴ I interpolate the annual estimates from the BLS MFP database. After the end of the

come from Fraumeni (1997), who provides estimates of geometric depreciation rates for 31 types of equipment and 15 types of structures. (We use Bureau of Economic Analysis, 2004, for medical and nonmedical instruments.) We aggregate to the level of four types of equipment and one type of structure using as weights the estimated nominal value of the stock of capital of each detailed type. For inventories, the data come from NIPA Tables 5.7.5A, 5.7.5B, 5.7.6A, and 5.7.6B.

¹³ Other includes communication equipment, medical equipment and instruments, nonmedical instruments, photocopy and related equipment, and office and accounting equipment.

¹⁴ Calculated from capital tables.xls obtained from <http://www.bls.gov/mfp/mprdownload.htm>, (downloaded May 7, 2007). Estimate is the average share from 1987-2005. The BLS has separate tables on an SIC basis (which

BLS sample, I extrapolate assuming the annual values follow an AR(1) process). Since land use is a smooth and slow moving series, the approximation error from the interpolation is likely to be small.

I assume that capital input of a particular type of capital is proportional to $K_{j,t}$, the stock of that type of capital as of the beginning of the quarter. (With annual data, it is common to assume that capital input is the average of the capital stock in years $t-1$ and t . This mid-period convention seems less appropriate for quarterly data.)

To go from disaggregated capital stocks to a composite capital input measure, the standard first-order conditions for firm optimization imply that we need to weight by service flows. Implicitly, the nominal value of the service flow from a given type of capital j depends on the user cost R_j of that type of capital multiplied by the stock of that type of capital, i.e., $R_j \cdot K_j$. Standard first-order conditions for capital imply that the user cost is $R_{jt} = (i_t + \delta_j - \pi_{jt+1}^e)P_j^I$, where i is the nominal interest rate, π_{jt+1}^e is the expected rate of price appreciation for asset j between today and next period, and P_j^I is the purchase price (investment price) for asset j .

Given an estimate of the user costs, the Tornquist index of the service flow from aggregate capital input is defined as:

$$\Delta \ln K = \sum_j \frac{[s_j(t) + s_j(t-1)]}{2} \cdot \Delta \ln K_j$$

where the nominal shares in each period are $s_j = \frac{R_j \cdot K_j}{\sum_j (R_j \cdot K_j)} = \frac{(r + \delta_j - \pi_j^e) \cdot P_j^I \cdot K_j}{\sum_j (r + \delta_j - \pi_j^e) \cdot P_j^I \cdot K_j}$.

To calculate the user cost, we need measures of expected asset-specific price appreciation π_{jt+1}^e as well as nominal interest rate series. For expected price appreciation, I experimented with several end in 2002—check??) and NAICS basis (which start in 1987). I splice the land-input series together using growth rates, so that land input growth from 1948-1987 is from the SIC data, and from 1987 on is from the NAICS data.

methods. To start, suppose we assume rational expectations. Then actual inflation (between periods t and $t+1$) should equal ex ante expected inflation plus white noise error. This reasoning suggests that it should be reasonable to use actual asset inflation as our estimate of expected inflation. Unfortunately, since ex post asset inflation is sometimes extremely volatile, this measure leads to implausibly volatile shares s_j from quarter to quarter. As another approach, I estimated a simple univariate autoregressive forecasting model of the asset price and used the fitted values. This led to smoother shares, but had the undesirable feature that the forecasting model changed each time the data was updated—leading to minor but undesirable revisions in capital input over the historical period. Moreover, it is implausible that agents knew the full-period model; and using a recursive method (i.e., where only observations up through period t were used to forecast asset inflation for period $t+1$) implied having very few observations in the early years.

As a compromise, which led to a priori reasonable results, I estimated expected asset-price inflation using a centered 16-quarter moving average of price changes.¹⁵ This approach weights the recent past equally with the actual (unknown, but expected) future and has the a priori desirable property that asset weights s_j are relatively smooth from quarter to quarter. At the same time, these weights retain the genuine low-frequency movements, e.g, the shift towards information technology over time.

For the nominal interest rate, suppose we take the assumption of zero profits literally, so that all residual factor payments go to capital. There is then some implicit rate of return i such that the sum of factor payments is equal to output. As a residual, capital compensation is $P_K K = \alpha(PY - TPS)$. This compensation, in turn, equals the sum of payments to the different types of capital:

$$K_{comp} = \sum_j R_j \cdot K_{input,j} = \sum_j (i + \delta_j - \pi_j) \cdot P_j^I \cdot K_j . \text{ This equation implicitly defines the nominal interest rate } i: K_{comp} = i \cdot \sum_j P_j^I \cdot K_j + \sum_j (\delta_j - \pi_j) \cdot P_j^I \cdot K_j , \text{ or}$$

¹⁵ At the end of the sample, I drop the future observations since they are obviously not observed.

$$i = \frac{K_{comp} - \sum_j (\delta_j - \pi_j) \cdot P_j^I \cdot K_j}{\sum_j P_j^I \cdot K_j}.$$

Once we have a measure of the nominal interest rate i , we can calculate the user costs and relative weights for each of the types of capital. We can then calculate the growth in the index of capital input, giving us the key information necessary to map quarterly labor productivity into quarterly TFP.

Utilization

The disaggregated BLS hours-per-worker data necessary to make the BFK adjustment are available quarterly (or even monthly), matching our needs. I assume that the coefficients on hours-per-worker growth, at a quarterly frequency, match the annual BFK coefficients. This allows me to estimate a quarterly utilization adjustment that, when annualized, is extremely close to the BFK adjustment.¹⁶

There are a number of technical details. First, we need a full panel of estimates of industry hours per worker. This requires merging BLS data on hours per worker on an SIC basis (which were discontinued in April, 2003) with more recent data on a NAICS basis. The BFK estimates used SIC classifications, so we generally use the NAICS data to extrapolate the SIC data beyond 2002. We also need to estimate some series for the earlier years. In particular, the SIC data for construction and manufacturing industries are generally available as of 1947 (sometimes earlier); much of the non-manufacturing, non-construction data begin only in 1964 or, in some cases, even later. BFK-augmented values that aren't available from the BLS with annual data from Dale Jorgenson; since these data are not

¹⁶ There are some nevertheless some differences. For example, in some cases, BLS data are not available for the full sample period or for all detailed industries; in those cases, BFK augmented the BLS data with annual estimates provided by Dale Jorgenson. Those data are not available quarterly, necessitating different adjustments. Nevertheless, the utilization estimate is extremely close to the BFK estimate.

available quarterly, we instead use the available industry data to extrapolate series backwards. More specifically:

- In the BLS data, hours data for both instruments and electrical equipment begin only in 1988; from 1988-2003, the correlation of hours in industrial machinery with hours in electrical equipment is above 0.9, and the correlation with instruments is above 0.8. Hence, for the 1988-2003 period, I project hours per worker in both electrical equipment and in instruments on hours per worker in industrial machinery, and then use the fitted values back to 1947. In addition, there is also no separate instruments industry in the NAICS data (it is part of electronics), so we extend the instruments category with data on computer and electronic products.
- For transportation, information (i.e., communications), and utilities, there are disaggregated NAICS data back to either 1964 or 1972, but only aggregated SIC data back to 1964. In those cases, we take the NAICS data as our primary dataset and backcast with the SIC data.
- Even on an SIC basis, data for most service industries begin only in 1964. We extract three principal components from the construction and manufacturing industries (22 total industries), and then project service hours on these principal components. For the earlier period, the fitted values from these projections provide an estimate of quarterly hours per worker for all industries.

Second, I bandpass filter the log of the quarterly hours-per-worker data by industry to obtain frequencies between 8 and 32 quarters, I then take first differences and multiply by the estimated industry utilization coefficient from BFK. This gives industry estimates of utilization change. I use annual weights from BFK to aggregate across industries. For the period before 1949, I use the 1949 values; similarly, after 1996, I use the 1996 values.¹⁷

¹⁷ BFK bandpass filter annual rather than quarterly data, which leads to a slight difference in the estimated trend and, hence, in the estimated utilization series.

Third, we use coefficients estimated in BFK to create an industry utilization series. Finally, we use annual BFK industry weights to aggregate.:

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Figure 1

Comparing Annualized Quarterly TFP to the BLS Multifactor Productivity (MFP) Series

Two Measures of Factor Productivity

Annual percent change

Percentage

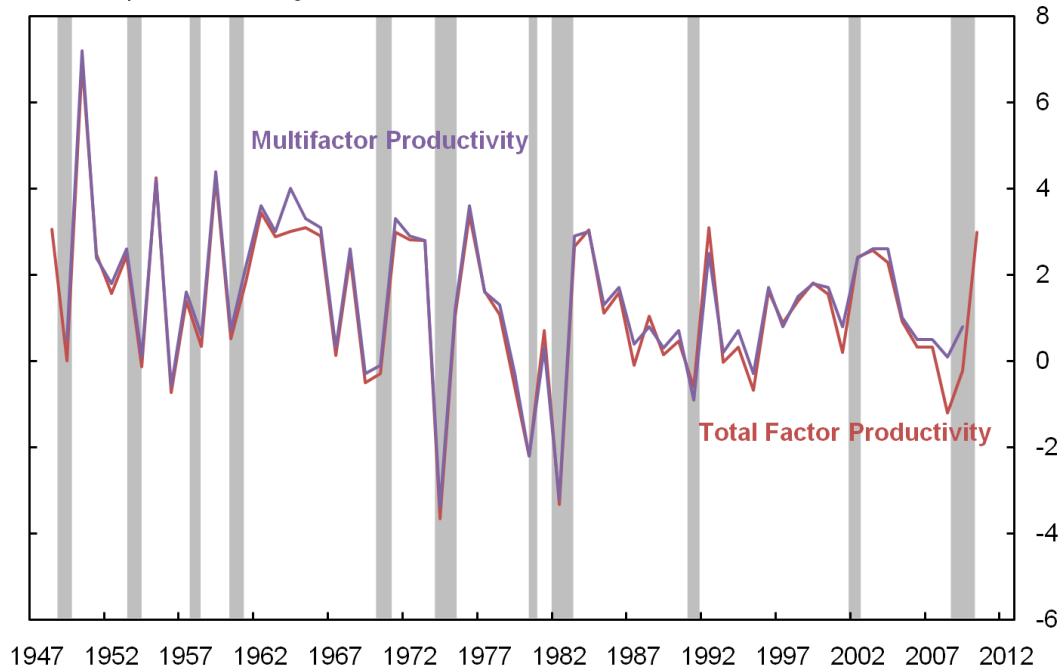
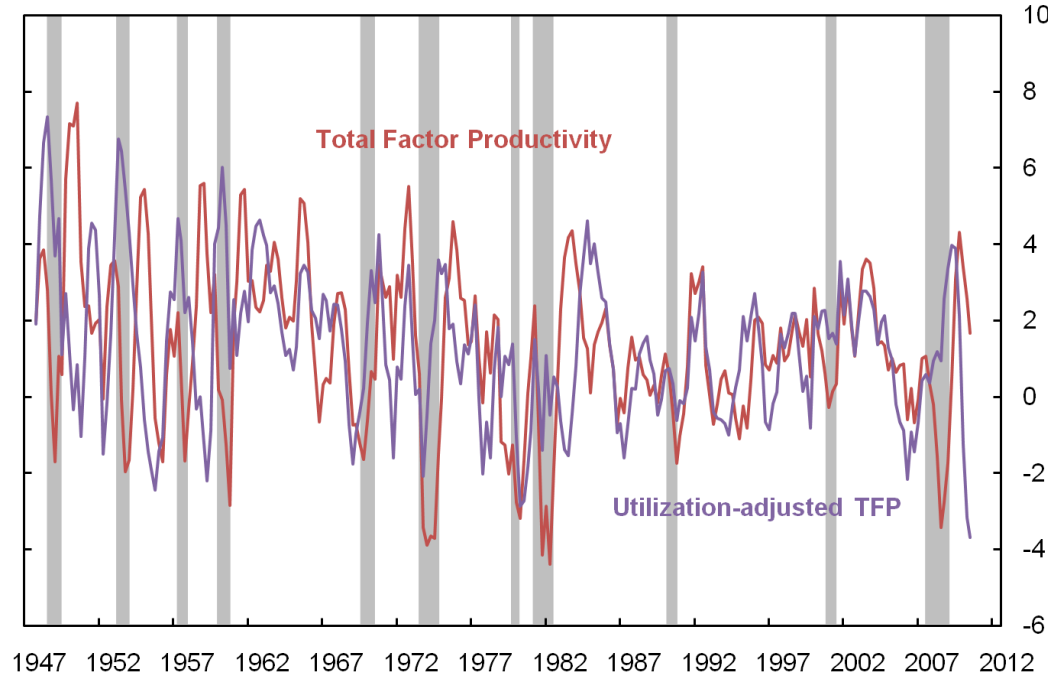


Figure 2: TFP and Utilization-Adjusted TFP

Two Measures of Total Factor Productivity

4-quarter percent change

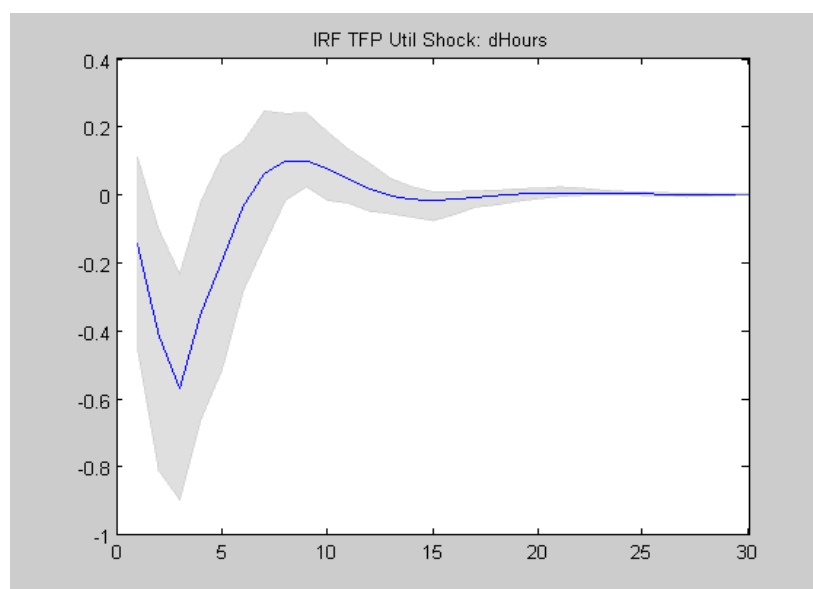
Percentage



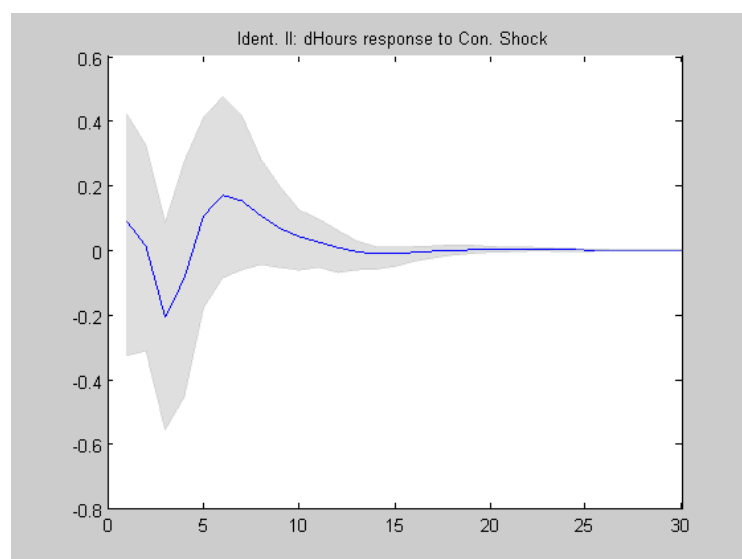
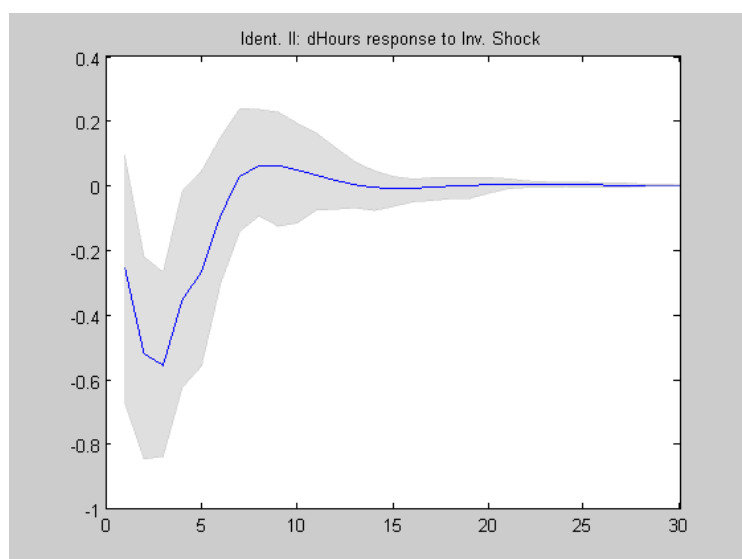
Source: Fernald (2011)

Figure 3: Impulse responses of hours worked to utilization-adjusted TFP shocks

A. Overall utilization-adjusted TFP



B. Utilization-adjusted investment and consumption TFP



Response of hours worked to a 1 percent shock to utilization-adjusted TFP. Estimated as a bivariate Cholesky identification, where current shocks to hours do not contemporaneously affect utilization-adjusted TFP. Bottom panel uses either consumption or investment technology.

Table 1: Means and Standard Deviations

Table 3: Regressions of output, hours, and investment on various measures of technology

| 1948Q1 - 2010Q4 | Utilization-Adjusted Total Factor Productivity | | | Utilization-Adjusted Consumption TFP | | | Utilization-Adjusted Investment TFP | | |
|-----------------------|---|---------------------|---------------------|---|---------------------|---------------------|--|---------------------|---------------------|
| 3 Lags | Output | Hours | Invest (E&S) | Output | Hours | Invest (E&S) | Output | Hours | Invest (E&S) |
| <i>T</i> | 0.472*** (0.06) | -0.140** (0.07) | 0.290 (0.29) | 0.501*** (0.06) | -0.111* (0.07) | 0.296 (0.27) | 0.281*** (0.07) | -0.133** (0.06) | 0.283 (0.26) |
| <i>T-1</i> | -0.286*** (0.05) | -0.179*** (0.06) | -0.358** (0.18) | -0.268*** (0.05) | -0.152*** (0.06) | -0.296 (0.19) | -0.277*** (0.05) | -0.140*** (0.05) | -0.360** (0.15) |
| <i>T-2</i> | -0.181*** (0.06) | -0.166*** (0.06) | -0.700*** (0.22) | -0.170*** (0.07) | -0.143** (0.06) | -0.634*** (0.23) | -0.106* (0.06) | -0.112* (0.06) | -0.558*** (0.19) |
| <i>T-3</i> | -0.040 (0.06) | -0.082 (0.06) | -0.257 (0.21) | -0.018 (0.06) | -0.056 (0.07) | -0.241 (0.23) | -0.050 (0.06) | -0.061 (0.06) | -0.047 (0.16) |
| <i>R</i> ² | 0.261 | 0.097 | 0.053 | 0.271 | 0.071 | 0.044 | 0.178 | 0.110 | 0.052 |
| Notes: | ***, **, * correspond to significance at 1, 5, and 10 percent | | | | | | | | |
| | Data sources for RHS variables Fernald (2011), LHS variables from Haver analytics | | | | | | | | |

Note: Each column is a separate regression. The column heading (e.g., utilization-adjusted total factor productivity) corresponds to the right-hand-side variable, which enters in growth rates contemporaneously and with three lags (*T* to *T-3*). The left-hand-side variables are growth in output, hours, or investment.